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Teaching Machine Learning in Learning Factories with Industry 4.0 use-cases

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Abstract

Increasing Industry 4.0 implementations enable unprecedented transformations in production in particular in the way production systems are optimized. With this rapid digitization enabled by increasingly sophisticated Hardware and Software, modern production engineering faces the necessity to include Artificial Intelligence and Machine Learning into teaching curricular. Based on an abundance of data that lends itself to acquisition and analysis, future production engineers need to identify, visualize, improve or even optimize solutions in real production environments. Learning factories evolved against the background of empowering participants with hard skills acquired in such environments. A plethora of approaches apply Machine Learning concepts to visualize, demonstrate or explain Industry 4.0 implementations. However, the availability of a real production environment for hands-on hard-skill based Machine Learning teaching in different Industry 4.0 use-cases has rarely been of interest so far.

Hence, this paper presents a structured approach for teaching Machine Learning in the Learning Factory Global Production by implementing Industry 4.0 use-cases. This acquaints participants with the structured CRISP-DM approach and a variety of Machine Learning techniques in theory and practice with increasing complexity. The presented approach culminates in empowering novel use-case implementation by participants and is validated in the Global Production Learning Factory.

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1. Motivation

Nowadays, digitization is attracting more and more importance and is becoming a central component of society. Production is an important example as manufacturing companies face the challenges and opportunities of the fourth industrial revolution: Industry 4.0, ever present mass customization, increasingly sophisticated hard- and software and the need to consistently train and engage with the workforce [8, 7] for production system optimization purposes. In this context, the amount of data generated or collected in production is increasing and opens the opportunity to increase the efficiency of entire production systems [14]. Machine Learning (ML) methods are predestined for processing and

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using this data. Machine Learning enables analyses of large amounts of data and opens up potentials for intelligent production in times of Industry 4.0 [9]. The conversion of data into usable and insightful information, in turn, offers new insight into existing processes as well as performance measurements for large systems in real time [14].

In line with this transformation in industry [8, 7], a transformation is also taking place in so-called learning factories. By working through production processes using these real products on site, students and professionals can effectively understand learning content and perceive an awareness of the consequences of their actions [11]. Most importantly, including ML into curricula [13, 7] for the engineers of the future remains a challenge that can be solved with hands-on teaching Machine Learning in Learning Factories with Industry 4.0 use-cases. Thus, reaping the benefits of ML applications in production requires engineers to have the right knowledge. Hence, for the industry and future engineers tangible experiences with ML become valuable and both industry and teaching have to adapt.

Based on the CRISP-DM model (CRoss Industry Standard Process for Data Mining) [16] and Kolb's Learning Cycle [10], this paper introduces a novel concept for teaching Machine Learning in Learning Factories by hands-on solving increasingly complex Industry 4.0 use-cases on the Shopfloor of the global learning factory which uses electric motors as training products [11]. The paper is structured as follows: Section 2 presents an overview of Machine Learning applications and teaching approaches in Learning Factories, thereby showing the need to join Machine Learning, Learning Factories and Learning Theory. Our own approach is then presented in Section 3 and one of the use-cases and results is in-depth presented in Section 4. Finally, Section 5 discuss the findings and provides an outlook.

2. Related Work

2.1. Learning Factories

The interest in learning factories is steadily increasing, and at the same time a change within learning factories is emerging. From an educational discussion about the right teaching approaches to the development of advanced learning factories that deal with the topics of Industry 4.0, virtual environments and Artificial Intelligence [13]. Based on this, various approaches currently exist in learning factories to improve students' Machine Learning skills. One approach is to prepare participants in general for working in Machine Learning environments by raising necessary awareness, without the explicit implementation of use cases and programming parts [2]. The most common approach is to implement singular ML applications with the help of students in learning factories, which improves existing learning factories and, on the other hand, enables students to apply ML methods in an industry-oriented way [7]. On this basis, further students try out the applications already created and, building on this, develop new tools themselves. This process improves the skills of the participants in a practice-oriented manner and drives the digitization of learning factories further, for instance in compliance detection [1] or waste identification [5], vision based quality control [12] or machine vision [19], machine data analysis [17] and bottleneck identification [6]. Another approach is the structured teaching of students on the basis of one elaborated use case [3, 18]. However, a holistic approach that reunites different ML approaches with learning theory based on several use cases is missing. Thus, the goal of this research is to present an extensible, prior knowledge free step into the ML cosmos on the basis of several use cases in a learning factory.

2.2. Kolb's learning cycle

Learning theory can be seen as major reason for the success of Learning Factories, in particular as they often implement experiential learning, where students learn from application and experiences [10]. This can be best described with Kolb's learning cycle [10], which provides an iterative process that starts with "Do" (Concrete experience), is followed by "Think" (Observations and reflections), which is followed by "Conclude" (Formation of abstract concepts and generalisations) and leads to "Adapt" (Testing implications of concepts in new situations) [10]. The circle achieves iterative behavior, as the "Adapt" phase can be followed by another "Do" phase where experiences from these adaptions are acquired [10]. Kolb's learning cycle is also visualized in the core of Figure 3. As this learning is essentially based on experience, acquiring experience for participants shall be of utmost importance for the developed approach, which will be based on Kolb's learning cycle.

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2.3. Image Recognition

Recognizing images is a typical use case in Learning Factories that employs ML [6, 19], which is often performed with Convolutional Neural Networks (CNN). By consistently adapting the CNN architecture results have been increased tremendously, for instance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) the classification error rate has dropped from over 26% to under 2.3% in six years. In particular potent models, such as the Xception model emerged [4]. Thus, image recognition shall serve as a case study of the presented approach.

3. Own Approach

Based on the outlined research question of using Kolb's learning cycle [10] and the underlying idea of combining both the ML and production engineering world in a learning factory, several requirements can be derived:

1. A structured approach according to the CRISP-DM model [16]
2. The integration of supervised, unsupervised and reinforcement learning [4]
3. Covering Machine Learning basics, such as overfitting and definitions of evaluation measures [4, 15]
4. The integration of several different ML methods and algorithms [5]
5. Participants learn practical and industry-related skills [13]
6. Application of Python as the most widely used programming language in the field of ML [15]
7. No prerequisites and, thus, Python and ML theory introduction [4]
8. Independent participant research as new libraries and code continue to emerge in Python [15]
9. Multiple use-cases [7, 11] and extendable ML algorithms [14]
10. Apply the learned skills in group work on independently recorded data in the environment of the learning factory to deepen the previously learned skills and to generally contribute to an improvement in learning factories

Building on these principal requirements, the developed teaching course implements as Python (req. 6 & 7) and ML theory basics introduction (req. 2 & 3) which is followed by various Industry 4.0 applications (req. 5) that apply the CRISP-DM framework (req. 1). Each of these applications introduce more complex ML models (req. 2 & 4), problem sets (e.g. data types and classification or prediction) and Python ML libraries or code (req. 8 & 9) with which the participants can gain ML experience based on Kolb's learning cycle ("Do → Think → Conclude → Adapt → Do → ..."). Therefore, at first, general and method-specific theoretical basics, which are required for the use of the ML method, are taught. Afterwards the participants have the possibility to implement this knowledge in prepared Python scripts ("Do"). This is followed by evaluating the preliminary results ("Think"), researching possible underlying reasons ("Conclude") and solutions to overcome these suboptimal evaluations ("Adapt"). Alleviating these shortcomings by once more following once cylce, until an acceptable result threshold is reached, ensures profound experiences, independent research and contributes to use-case improvements (req. 10).

All Python scripts contain their own tasks for each student. These are for example gaps in the code or the adaption and inclusion of hyperparameters, for obtaining better results. The goal is to teach participants how to use ML (on a coding level) and to enable them to implement solutions themselves by building on existing frameworks. Furthermore, the students are able to recognize in which cases which ML method is suitable and where limitations exist. Thus, all in all four use-cases int the global learning factory [11] are integrated into the course according to an ascending level of difficulty (Figure 1).

In order to validate the results the course has been established and a case study is implemented, which regards Use-Case 4 (Visual Inspection) and shows the participants improvements over time as well as their learning journey following Kolb's learning cycle.

4. Case Study: Use-Case 4 - Visual quality detection

In the following section, the identification and implementation of a use case for Machine Learning within the learning factory at the wbk is presented exemplarily.

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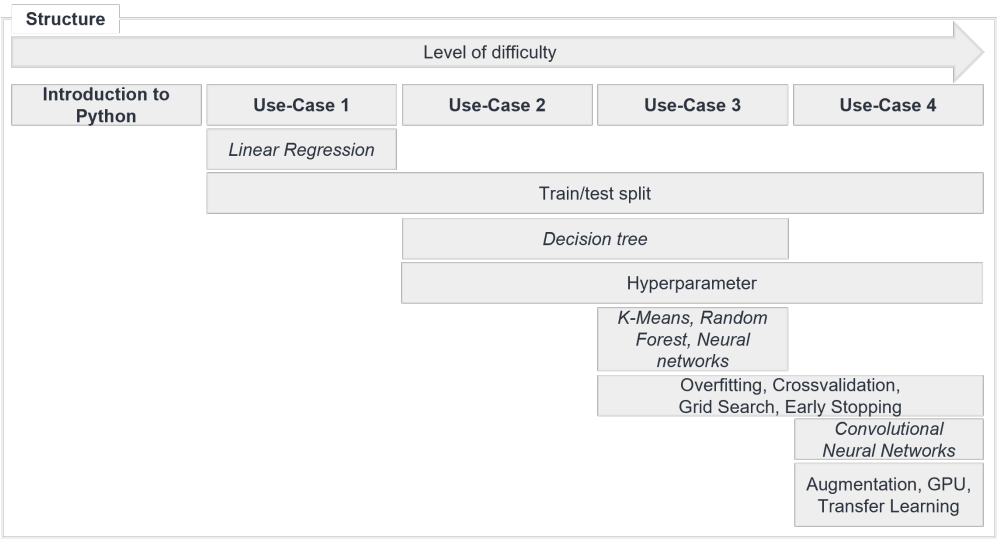

Fig. 1. Use-case based structure of the developed ML course for learning factories

Station 1 in the global learning factory [11] causes the majority of errors in the assembly of electric motors. At the station, two magnets are pressed into a pole pot with the help of two spring clips. Thus, in following processes potential errors of station 1 become invisible and only emerge when testing the final product. Hence, decreasing the scrap rate or at least ensuring functional products are processed in successive stations is decisive for the entire learning factory efficiency. The process at station 1 is divided into the following steps. The first step is the insertion of the spring clips and magnets. Then the pole pot is slid over the magnets and in the next step the press is actuated. This pushes the pole pot and magnets over the spring clips, fixing the magnets inside the pole pot. The final process step of the station is manual optical quality inspection. The assembly group is *okay (OK)* when both magnets and springs are fully pressed to the bottom of the pole pot. Figure 2 on the left shows a assembly group that is OK, whereas Figure 2 in the center and on the right shows assembly groups that are *not okay (NOK)*. The assembly group in the center is NOK because the magnet at the top of the image is not fully pressed in the pole pot. In the right assembly group, both the lower magnet and the two springs are not pressed correctly.

Fig. 2. Assembly group after passing station 1 - Left: OK. Center: NOK. Right: NOK.

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The press is relevant to the cycle time during operation and represents a bottleneck [6]. Therefore, the process result and the effectiveness of the entire production system are directly related to the press. From this problem, the objective of the business understanding phase is derived. The goal is to develop a ML algorithm that recognizes whether the assembly group is OK or NOK. This corresponds to a classification problem with two classes OK and NOK. On this basis, NOK components can be sorted out early. In addition, there is no need to transport sorted out NOK assembly

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groups to subsequent stations. This corresponds to a reduction in the wastefulness of the transport (and consequently processes). In addition, no problems arise at subsequent stations due to incorrectly pressed assembly groups.

The goal of the application is to replace and improve manual optical quality inspection by image processing. For this reason, 200 OK images and 200 NOK images were acquired. For this purpose, the process step at Station 1 was performed repeatedly. After a manual optical quality control, the assembly group was labeled OK or NOK. Every imaginable defect was included in the image recording as at least one example. The data is then processed so that an ML algorithm could be trained using the data (Data Understanding and Preparation). For this purpose, the acquired images are first transformed into a unified form of 224 × 224 pixels, following the ImageNet competition. One-hot-encoding is performed on the output data (OK as 1 and NOK as 0). Then the data is split 80% into a training dataset and 20% into a separate test dataset, so that the CNN-based ML model can be trained.

After the students have understood the use-case and the theoretical basics of CNNs, following the Kolb's learning cycle, the students generate deeper insights into the functionality of CNNs. Starting with a simple network structure, students identify opportunities for improvement based on various assessment measures. With the help of additional theoretical principles, the students implement the improvements in the existing code and, thus, try to continuously advance the results. Kolb's learning cycle is iterated through, whereby the students gain a deeper understanding of the modeling of Machine Learning problems, as explained in Figure 3.

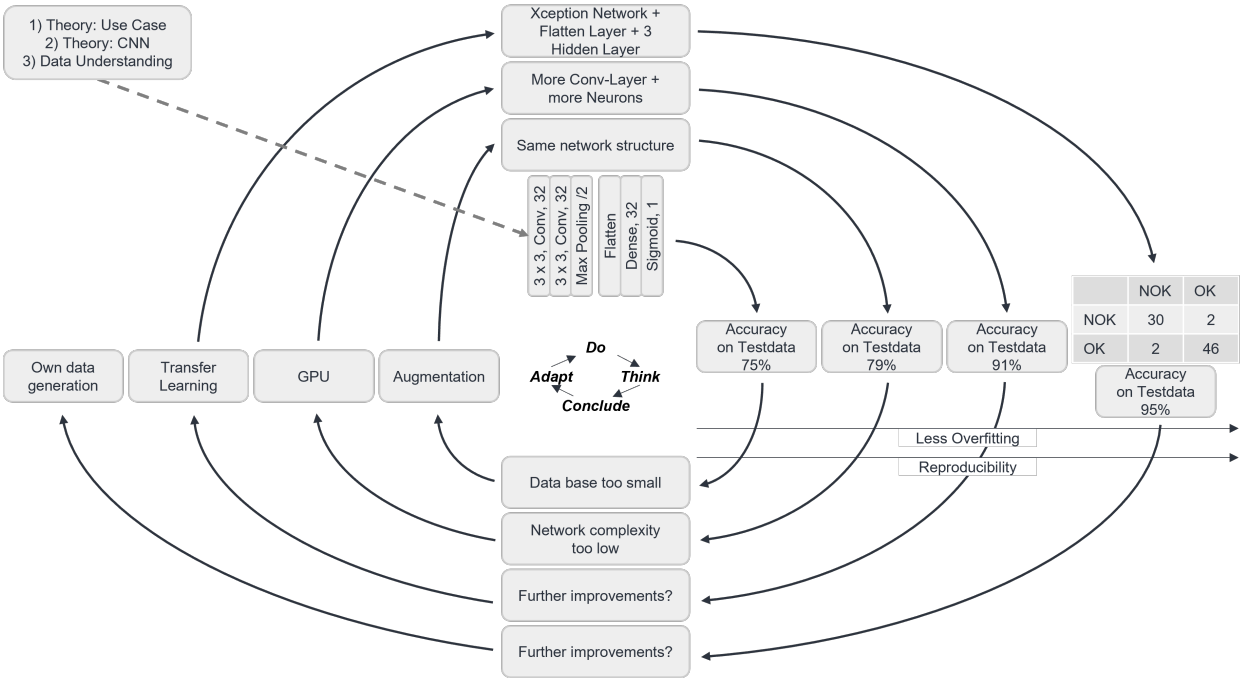

Fig. 3. Iterating Kolb's learning cycle in the Image Recognition use-case

Finally, the participants take their own pictures and, hence, advance on the next, independant research level. As the setting is in a learning factory, thw course addresses mainly participants with a production engineering background. Following the teaching concept of experiential learning [10], the participants integrate their previous experiences in the production environment into the image acquisition. One possibility is the use of a caliper gauge. This makes it possible to measure the distance between the top edge of the pole pot and the pressed-in magnets and springs. This additional information enables a more precise statement from a quality point of view as to whether the assembly group is OK or NOK. Building on these considerations, the participants generate new experience in the area of Machine Learning by independently solving the classification problem based on the new data. All in all, this leads to high student satisfaction and sustainable learning outcomes as well as steady Industry 4.0 use-case improvements in the learning factory.

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5. Summary and Outlook

The approach for teaching ML in learning factories developed in this work provides students with production-related ML experiences. Based on Kolb's learning cycle participants acquire increasingly complex knowledge and are able to solve increasingly hard ML problems. The case study shows good results by presenting an exemplarily developed use-case. Due to new use cases and a rapid ML development constantly updating courses and content in the framework should be regarded. Furthermore, reinforcement learning manufacturing applications can be integrated.

The application of Machine Learning can help production systems to quicker fulfill customer needs, become more efficient or reduce scrap. Thus, regarding sustainability issues in manufacturing with ML in learning factories is increasingly important. Moreover, the approach could be transferred to other topics than ML in learning factories.

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